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Predicting Risk Sensitivity in Humans and Lower Animals: Risk as Variance or Coefficient of Variation

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This article examines the statistical determinants of risk preference. In a meta-analysis of animal risk preference (foraging birds and insects), the coefficient of variation (CV), a measure of risk per unit of return, predicts choices far better than outcome variance, the risk measure of normative models. In a meta-analysis of human risk preference, the superiority of the CV over variance in predicting risk taking is not as strong. Two experiments show that people's risk sensitivity becomes strongly proportional to the CV when they learn about choice alternatives like other animals, by experiential sampling over time. Experience-based choices differ from choices when outcomes and probabilities are numerically described. Zipf's law as an ecological regularity and Weber's law as a psychological regularity may give rise to the CV as a measure of risk.

Decision making under risk and uncertainty is a topic of research in disciplines as diverse as psychology, economics, zoology, and entomology. Both the animal and the human risky choice literatures have proposed models that either predict choices in a deterministic fashion or predict risk sensitivity (i.e., the probability of choosing a riskier or less risky option) in a stochastic fashion. Theories of human risky choice include the prescriptive expected utility model (von Neumann & Morgenstern, 1947) or the risk–return models used to price risky options in finance (Markowitz, 1959). A prominent descriptive model is prospect theory (Kahneman & Tversky, 1979). In the animal literature, theories about risky foraging gave rise to the energy budget rule (Caraco, 1980; Stephens, 1981), a special case of a general class of normative models called risk sensitivity theories that construe risk sensitivity as the response of organisms whose goal is the maximization of Darwinian fitness in stochastic environments. Similar to prospect theory for human risky choice, the energy budget rule predicts risk aversion when animals are not in danger of starvation (domain of gains) but risk seeking when there is such a risk (domain of losses).

Although different in many respects, these models all assume that the likelihood of choosing a risky option is affected by the variability of the option's possible outcomes. The measure of variability used in these models is usually the variance of outcomes around the option's expected value. The capital-asset-pricing model in finance, for example, equates risk with variance and predicts that people's willingness to pay for risky options with equal expected value is a decreasing function of the options' outcome variance (Sharpe, 1964). The energy budget rule, as another example, predicts that—among options with equal expected energy intake—animals will prefer foraging options with smaller variance when the expected energy intake exceeds the caloric needs of the animal but will prefer options with greater variance when the expected energy intake is less than that required for survival because increases in outcome variance (holding expected value constant) are associated with a greater chance of obtaining the caloric intake required for survival.

However, observed levels of risk sensitivity for humans as well as other animals often deviate from the predictions of these models (see Kacelnik & Bateson, 1996, and Shafir, Wiegmann, Smith, & Real, 1999). Human risky choice data (e.g., E. U. Weber, 1988; E. U. Weber & Milliman, 1997) suggest that the predictive shortcoming of these models stems from their use of outcome variance as a measure of risk. Variance seems to be the wrong measure of risk for some reasons that have been discussed elsewhere (Luce & Weber, 1986).[1] In this article, we address an additional shortcoming of outcome variance (or standard deviation) as a measure of risk that relates to the fact that people (and other animals) may perceive and encode outcome variability not in an absolute fashion but relative to the average level of outcomes. Like E. U. Weber (1999; E. U. Weber & Hsee, 1999) in a different context, we argue that characteristics of the subjective perception of outcome vari-

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[1] One important problem is that variance treats deviations above and below the mean symmetrically, even though most people are vastly more concerned with variability below the mean than variability above the mean when judging risk (e.g., Bontempo et al., 1997).

ability need to be considered to arrive at accurate predictions or interpretations of behavior in risky choice situations.

To make this point, we take a brief detour into psychophysics. Psychophysical investigations of people's judgments of simple sensory continua (e.g., loudness, brightness) show that the difference in stimulus magnitude required to see two stimuli as different grows in proportion to the stimulus to which the difference is added (E. H. Weber, 1834/1978). This difference (called *just noticeable difference* [JND]) provides a measure of discriminability in psychophysical judgments. Weber's law describes the fact that the JND grows proportionately to the absolute level of stimulus magnitude. Marsh and Kacelnik (2002) applied Weber's law to risky choice. Their scalar utility theory (SUT) makes use of Gibbon's (1977) scalar expectancy theory in assuming that variability in animals' perception of reinforcement amounts and delays is proportionate to their magnitude (Gibbon, Church, Fairhurst, & Kacelnik, 1988). Bateson and Kacelnik (1995) provided some empirical evidence that the internal representation of food amounts in starlings follows Weber's law in this fashion.

Savage (1954, p. 103) applied the logic of Weber's law to the evaluation of outcome differences in the context of riskless choice, describing a regularity in people's subjective evaluation of outcomes subsequently called percentage framing (Thaler, 1980), in which a difference in outcome values is judged proportionately to the magnitude of the reference outcome. Thus, a \$100 price reduction seems significant when buying a \$200 pen (a saving of \$100/\$200 or 50%) but trivial when buying a \$20,000 car (a saving of only \$100/\$20,000 or 0.5%). Whereas outcome framing relative to a reference point (Kahneman & Tversky, 1984) involves a cognitive operation that computes a difference and results in a relative evaluation of positive or negative valence, the percentage framing of outcomes involves a cognitive operation that computes a ratio and results in a different evaluation of relative magnitude. Such ratio comparisons are not restricted to just human comparisons of money savings. Gallistel and Gelman (1992) reviewed a large amount of evidence that suggests that rats' comparisons of numerosities involve ratio operations and that animal number and duration discrimination conforms at least qualitatively to Weber's law.

In combination, these results suggest that the coefficient of variation (CV), a measure of the relative variability of risky choice alternatives that is calculated by dividing the standard deviation (SD) of outcomes by their expected value (EV; and often multiplying it by 100 to express the SD as a percentage of the EV), might be a better predictor of risk sensitivity than the unstandardized variance or SD. The CV is, indeed, widely used as a measure of relative risk—risk per unit of expected returns—in applications that include engineering (e.g., Abacus Technology Corporation, 1996), medicine (e.g., Wennberg & Wennberg, 2000), agricultural economics (e.g., Johnson, Williams, Gwin, & Mikesell, 1986), archaeology (Crowther & Barker, 1995), and financial management (Gunther & Robinson, 1999; Rajgopal & Shevlin, 2000). Monitoring systems that evaluate human performance or the performance of physical systems (e.g., manufacturing processes, radon measurement) use the CV as their preferred measure of the system's precision; in such applications, the CV is often called the *relative standard deviation* (Rector, 1995). Thus, it is surprising that, until very recently, it has not been examined as an index of risk in risky choice.

Aside from greater psychophysical plausibility as a measure of perceived variability or risk, the CV has the advantage of allowing comparisons of risk sensitivity across choice situations that differ in range (e.g., the weight of mice vs. the weight of men) or outcome dimension (e.g., weight vs. height). Dividing the SD by the EV makes the CV dimensionless (i.e., cancels out the dimension of obtainable outcomes, e.g., dollars or time spent), an advantage for comparative analyses that has not gone unnoticed by methodologists in ecology or other applied research areas (Hilborn & Mangel, 1997).[2] It is precisely the possible cancellation of measurement units in the numerator and denominator that makes the CV a more attractive standardization of relative risk than the division of variance by EV.

Of Bees and Men: The Utility of Cross-Species Comparisons of Risk Taking

The animal literature on risky decision making, including risk-sensitive foraging, ought to hold lessons for human decision making under risk and uncertainty. Human responses to risky situations derive, at least in part, from the same mechanisms evolved by other animals in response to the stochasticity of their natural environment. In addition to learning on an evolutionary scale, learning on an ontogenetic scale is involved in shaping the behavior of humans and other animals in risky environments (Thorndike, 1898; Williams, 1988). However mediated, many similarities in the decision behavior of humans and other animals have been documented, including matching rather than maximization behavior (e.g., Commons, Herrnstein, & Rachlin, 1982) and violations of the postulates of the expected utility model, in particular intransitivity of preferences (Shafir, 1994) and the Allais paradox (for a review, see Real, 1996).

Both cognitive and social psychologists have recently suggested dual process theories of information processing and reasoning (e.g., Chaiken & Trope, 1999; Sloman, 1996) that have been applied to judgment and decision making (e.g., Windschitl & Weber, 1999). These theories typically distinguish between rule-based processing, a relatively effortful and controlled form of processing that operates according to formal rules of logic and probably involves brain structures more developed in higher animals, and associative processing, a more spontaneous form of processing that operates by principles of similarity and contiguity and involves brain structures present in both humans and lower animals. To the extent that human decision making is mediated by associative rather than rule-based processing, one would expect similarity between choice patterns in human and animal data.

In this article, we take a two-pronged approach toward examining the similarities and differences in risk sensitivity exhibited by humans and other animals. First, we compare the results of a meta-analysis of human risk-preference data with the results of a

[2] One drawback of the CV is that it is undefined for risky options that have an EV of zero. This is not a problem for the risky options described in this article that have outcomes either in the domain of gains (with EVs greater than zero) or in the domain of losses (with EVs less than zero). For mixed lotteries with the possibility of an EV of zero, there is evidence that people evaluate the positive and negative components separately and subsequently combine their evaluations of the two components, as modeled by cumulative prospect theory (Tversky & Kahneman, 1992).

similar meta-analysis of animal data by Shafir (2000), who found the CV to be a better predictor of risk sensitivity than variance. Second, we report the results of two experiments. Experiment 1 places humans (undergraduates at the Ohio State University) in a risky learning and decision-making situation as comparable as possible to risky foraging choice tasks in animal experiments. The outcomes of choice alternatives and their likelihood have to be learned by repeated sampling over time, and the goodness of each alternative is presumably established by associative learning. In Experiment 2, a different set of human respondents solved the same choice problems in a way typical for most human risky choice experiments: That is, they were given outcomes and choice probabilities in the form of a pie chart for each choice alternative. As our results show, choice behavior was very different in the two studies. The CV described risk sensitivity very well in Experiment 1, in which information was acquired by associative learning.

Some Caveats

Most models of risky choice, including the expected utility model of human risky choice or the energy budget model of animal foraging, merely aspire to predict choice behavior as a function of general characteristics of the outcomes of the choice alternatives. They are moot on the processes by which hypothesized choice regularities may arise. For such models, the main argument of our article is that variability of outcomes is a relative concept and that its relative nature is best captured by standardizing the SD of outcomes by the choice option's EV. We show that the resulting measure, the CV, is a better statistical predictor of risk sensitivity than either the SD or the EV alone or in an additive combination. This regularity can be demonstrated and used predictively without any assumptions about the processes that would give rise to it.

This is not to say that process models do not exist. Kacelnik and collaborators have recently provided process model candidates that account for observed regularities in the risk sensitivity of birds and other foragers as a function of variability in outcome amounts as well as outcome delays (Kacelnik & Bateson, 1996). One such model, SUT (Marsh & Kacelnik, 2002), applies Weber's law to animals' internal representation of perceived or expected outcomes. An amount of a particular magnitude is represented by a normal probability density function with a mean and SD that are both proportional to the amount, resulting in a constant CV across magnitudes. The representation of a gamble is the (subjective probability or relative frequency) weighted sum of the representations of the different possible outcomes. Together with some assumptions about how two risky options are compared to arrive at a choice (Kacelnik & Brito e Abreu, 1998),[3] SUT predicts risk aversion for choices among options perceived as desirable (in which more is better) and risk seeking for choices among options perceived as undesirable (in which more is worse). Because of its use of Weber's law in its encoding and retrieval assumptions, SUT also predicts that risk sensitivity should be proportional to the CV rather than the variance of outcomes.[4]

As a second caveat, our emphasis on the relative nature of risk perception in this article neither addresses nor invalidates other concerns about variance as a measure of risk (Luce & Weber, 1986). Future studies with more complex risky choice options than two-outcome lotteries should look, for example, at a possible asymmetry in the effect of the upside CV versus downside CV (i.e., compute the positive and negative semi-SD of choice alternatives and standardize each by the options' EV).[5]

Finally, our postulate that the CV is a better predictor of risk sensitivity than variance does not question in any way that many variables other than outcome variability affect risk sensitivity. Some of those related to human decision making are further discussed with respect to the results of our meta-analysis of the human choice data. In the animal literature, other variables include species differences in social organization and/or resource utilization that affect the animals' utility for outcomes differing in volume, concentration, or delay (see Kacelnik & Bateson, 1996, 1998). Such variables can be expected to reduce the fit of models that predict risk sensitivity simply as a function of outcome variability in the form of the CV.

Empirical Evidence for CV Versus Variance as Predictor of Risk Preference

Meta-Analysis of Animal Data

Shafir (2000) demonstrated that predictions of risk preference for a wide range of animal foraging data are much improved by the use of the CV rather than the variance or SD of outcomes as a predictor variable. Shafir's meta-analysis included the studies reviewed in Kacelnik and Bateson (1996) as well as four more recent studies. Some studies consisted of a single experiment; other studies consisted of several experiments. In each experiment, foraging animals (wasps, bees, fish, and birds) had to choose between an option that provided a constant reward and an option that provided a variable reward with an expected value equal to the constant reward. Food rewards included sucrose solution of varying concentrations, seed pellets, and mealworms. In all cases, animals learned about the reward distribution offered by the two-choice alternatives by repeated exposures prior to the experimental choice trials. The dependent measure was the proportion of choice trials for which animals chose the alternative with the constant reward.[6] In 8 of these experiments, the energy budget was negative; that is, average available caloric intake was below survival levels. In the remaining 49 experiments, the energy budget was positive.

Use of the CV rather than variance or SD as the predictor of risk preference makes it possible to include experiments with different types of reward units in the same analysis because dividing the SD by EV makes the CV dimensionless. Thus Shafir (2000) was able

[3] The simplest one involves drawing a sample from the representation of each option and choosing the option that provides the sample with the higher value.

[4] Kacelnik and Bateson (1996) identified associative learning processes as an alternative explanation to SUT for risk seeking observed among animals for delays of reinforcement. As we show below, associative learning models also have the property of predicting risk sensitivity that is proportional to the CV rather than the variance.

[5] The results of our meta-analysis of human choice data reported below suggest that such additional refinements will, in fact, be necessary.

[6] In our analysis of the animal and the human data, the implicit assumption is that respondents are homogeneous, which allows us to aggregate across respondents and to analyze group choice proportions as the dependent measure.

to include different species of foragers (nectarivores and nonnectarivores) and types of reward (nectar differing in volume or concentration or solid food rewards such as seeds or mealworms differing in number) in his meta-analysis.

Because the expected value of rewards was the same within each pair of choice options, risk–return models of choice (including the energy budget rule) predict that preference for the constant reward option is a function of the variability of the variable reward option. More formally, the expected utility of a risky option X, $E[u(X)]$, can be expressed as a trade-off between the utility of an option's EV and its risk (R; Bell, 1995):

$$E[u(X)] = u[EV(X)] - bR(X). \tag{1}$$

For a quadratic utility function u, $R(X)$ is equal to the variance. Other utility functions are consistent with other measures of risk (Bell, 1995; Jia & Dyer, 1997). The difference in utility between risky option X and sure option Y that is equal in value to $EV(X)$ is a linear function of $R(X)$:

$$E[u(Y)] - E[u(X)] = u[EV(X)] - \{u[EV(X)] - bR(X)\} = bR(X). \tag{2}$$

If preference for sure option Y and the proportion of respondents choosing the sure thing, $p(\mathrm{ST})$, is proportionate to the difference in utility between choice options, then $p(\mathrm{ST})$ should also be an increasing linear function of the riskiness of option X, $R(X)$.

A similar result holds if we predict choice stochastically; for example, an exponential version of Luce's (1959) probabilistic response rule that is commonly used in adaptive learning research (e.g., Camerer & Ho, 1999) follows:

$$p(\mathrm{ST}) = \frac{e^{E[u(Y)]}}{e^{E[u(Y)]} + e^{E[u(X)]}} = \frac{e^{u[EV(X)]}}{e^{u[EV(X)]} + e^{u[EV(X)]-bR(X)}}$$

$$= \frac{e^{u[EV(X)]}/e^{u[EV(X)]}}{\{e^{u[EV(X)]}/e^{u[EV(X)]}\} + \{e^{u[EV(X)]-bR(X)}/e^{u[EV(X)]}\}} = \frac{1}{1 + e^{-bR(X)}}. \tag{3}$$

In this case, $p(\mathrm{ST})$ is an increasing logistic function of the riskiness of option X, $R(X)$, that can be approximated reasonably well by a linear relationship for intermediate ranges of X.

To test whether the dimensionless CV as a measure of perceived risk ($R(X)$) predicts strength of preference for sure option Y, Shafir (2000) regressed the proportion of choices favoring the constant reward alternative ($p(\mathrm{ST})$) on the CV, separately for both positive and negative energy budget experiments for which Caraco's (1980) normative risk-sensitivity model predicts different slopes, namely increasing risk aversion with variability for positive energy budgets and increasing risk seeking for negative energy budgets, as explained above. As shown in Figure 1, for positive energy budgets (circles), larger variability (CV) was associated with greater risk aversion: $p(\mathrm{ST}) = 0.53 + 0.001$ CV, $F(1, 48) = 22.13$, $R^2 = .33$, $p < .0001$. In light of the wide range of species and types of reward included in the regressions (which can all be expected to affect risk preference in addition to CV), these fits are impressive.

For negative energy budgets (squares in Figure 1), larger variability (CV) was associated with greater risk seeking, although only at a marginal level of significance: $p(\mathrm{ST}) = 0.52 - 0.0012$

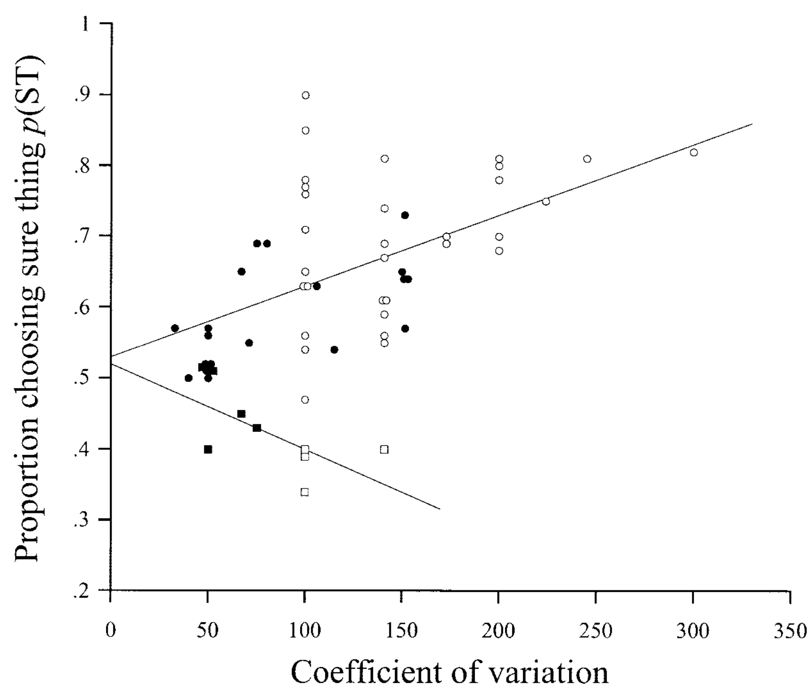

Figure 1. Proportion of animals choosing the constant award (sure thing) for experiments with positive energy budgets (circles) and negative energy budgets (squares). Experiments in which all options were rewarded (no zero outcomes) are shown as solid circles or squares, and experiments in which one of the risky outcomes was empty (zero) are shown as open circles or squares. From "Risk-Sensitive Foraging: The Effect of Relative Variability," by S. Shafir, 2000, *Oikos, 88,* p. 665. Copyright 2000 by Blackwell. Reprinted with permission.

CV, $F(1, 7) = 5.08$, $R^2 = .42$, $p < .10$. The number of data points available for this regression was small because methodological complications arise in experiments that examine foraging behavior in animals in a state of starvation (see Kacelnik & Bateson, 1996).[7] Thus, we have strong evidence that risk aversion for food amounts increases with the CV of the risky option under positive energy budget conditions. Methodological complications make it difficult to obtain sufficient empirical evidence to test whether risk seeking for food amounts is proportional to the CV (or other measures of variability) under negative energy budgets. Prospect theory (Kahneman & Tversky, 1979) suggests that decision makers are also risk seeking in the face of relative losses, that is, when obtained outcomes are not necessarily losses in an absolute sense but fall short of expectations—for example, a salary increase that is smaller than expected. Observing animal foraging behavior under such relative loss conditions requires some ingenuity but does not pose the same methodological complications as negative energy budgets. Marsh and Kacelnik (2002) recently observed risk seeking in starlings for such relative losses, but they used only a single-choice pair. Future studies using this methodology with a range of choices in which the variable options vary in variance and CV should allow for animal tests of risk sensitivity in the domain of losses.

Shafir (2000) also addressed whether risk preference is sensitive to outcome variability only in experiments with risky options that involve zero outcomes, a point of contention in the animal literature, in which some studies have reported such a difference in results (between risky choices that involve zero outcomes and those that do not) and other studies have found risk sensitivity in both kinds of experiments. To test for an effect of zero versus nonzero outcomes, Shafir combined both positive and negative energy budget experiments and computed risk sensitivity as deviations of p(ST) from .5. In an analysis of variance of this measure of risk sensitivity, a dummy variable coding for zero outcomes was not significant, $F(1, 53) = 2.12$, $p > .10$. Although null results always have to be interpreted with caution, it is at least plausible that the apparent effect of zero outcomes (open circles or squares in Figure 1) versus non-zero outcomes (solid circles or squares) in some studies is an artifact of the fact that studied zero-outcome choice options happen to have greater CVs, as shown in Figure 1, and that greater CVs result in greater risk sensitivity.

The advantage of using the CV as a predictor of risk sensitivity is that it allows for the inclusion of a large number of heterogeneous studies. The downside of using a disparate set of studies is that the relative ability of CV to predict choice proportions cannot be compared with that of other possible predictors such as the variance, SD, or EV of the outcomes of the variable award because these predictors are not comparable across studies that use different types of outcomes. We can provide this information, however, for a subset of experiments analyzed by Shafir (2000) that used the same type of respondent and reward. Choice proportions came from bees and wasps, and variability was in the volume of the reward, which was nectar of a particular concentration.

As shown in Figure 2, the CV accounted for a large proportion of the variation in risk sensitivity, $|p(\text{ST}) - .5| = -0.05 + 0.0015$ CV, $F(1, 10) = 25.00$, $R^2 = .71$, $p < .0005$, whereas the SD, $F(1, 10) = 0.00$, $R^2 = 0$, *ns*, and variance, $F(1, 10) = 0.13$, $R^2 = .01$, *ns*, did not. To examine the possibility that risk sensitivity is a function of the magnitude of the stakes (i.e., the expected value of the pair of choice alternatives, as suggested by Jia & Dyer, 1997) and that the CV is a better predictor of risk sensitivity because it incorporates the EV in its denominator, we regressed risk sensitivity on EV, measured by the sugar content of the nectar (sugar concentration $\times$ nectar volume). As shown in Figure 2D, mean sugar content of the nectar did not predict risk sensitivity, $F(1, 10) = 0.43$, $R^2 = .04$, *ns*. In summary, neither SD nor EV predicts risk sensitivity in isolation. Their ratio, however, in the form of the CV does so very well.

Meta-Analysis of Human Data

To test the ability of the CV to predict risk sensitivity in human respondents, we searched the literature on human risky choice for choice pairs that were similar in structure to the animal choice situations analyzed by Shafir (2000). A comprehensive search identified the 20 studies listed in Table 1, which provided a total of 226 choice situations with the following characteristics. Each situation presented a choice between either two gain options or two loss options. In all cases, one of the options assured a certain outcome; the other alternative had two potential outcomes that occurred probabilistically. The expected value of both alternatives was the same within each pair. The cited articles provided the proportion of respondents (out of each study's sample size, N) who chose the sure thing (p(ST)) in each choice pair as well as coding information about other variables, as shown in Table 1: respondents' gender, age category (young adults, older adults, or mixed), and nationality (American, Israeli, Chinese, Japanese, British, or Dutch); the substantive domain of the decision (money, time, human lives, etc.); whether the outcomes were framed as gains or losses; whether the risky option involved a zero outcome; whether respondents had received some advance payments with which to gamble (i.e., house money); and whether the choice was hypothetical or had real consequences.

We regressed p(ST), the proportion of respondents who selected the sure-thing choice alternative, on the list of predictor variables in Table 1.[8] In addition to these qualitative predictors, we used the following three quantitative variables as predictors of risk preference: the CV of outcomes in the risky choice alternative as a measure of relative risk, the probability of obtaining the lower of the two possible outcomes in the risky choice option as a measure of outcome skew, and the interaction between CV and skew as a proxy for the possibly asymmetric effect of upside versus downside variability on risk perception and thus risk sensitivity. Because all three of these predictors are dimensionless, we could examine their effect across a broad range of choice situations, combining choices in all substantive outcome domains into a single analysis.

A preliminary analysis confirmed the prediction of prospect theory (Kahneman & Tversky, 1979) that risk sensitivity (i.e., sign and magnitude of deviation of p(ST) from .5) depends more on relative outcome framing (outcomes larger or smaller than some expectation or reference point) than on the absolute sign of the outcome: relative gain versus relative loss, $F(1, 223) = 92.07$, $p <$

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[7] Five of the eight data points analyzed come from a single study (Caraco, 1980), in which birds received a relatively small number of training trials to minimize the consequences of a starvation energy budget.

[8] Because the dependent measures were choice proportions, we applied a logistic response transformation in all regression analyses.

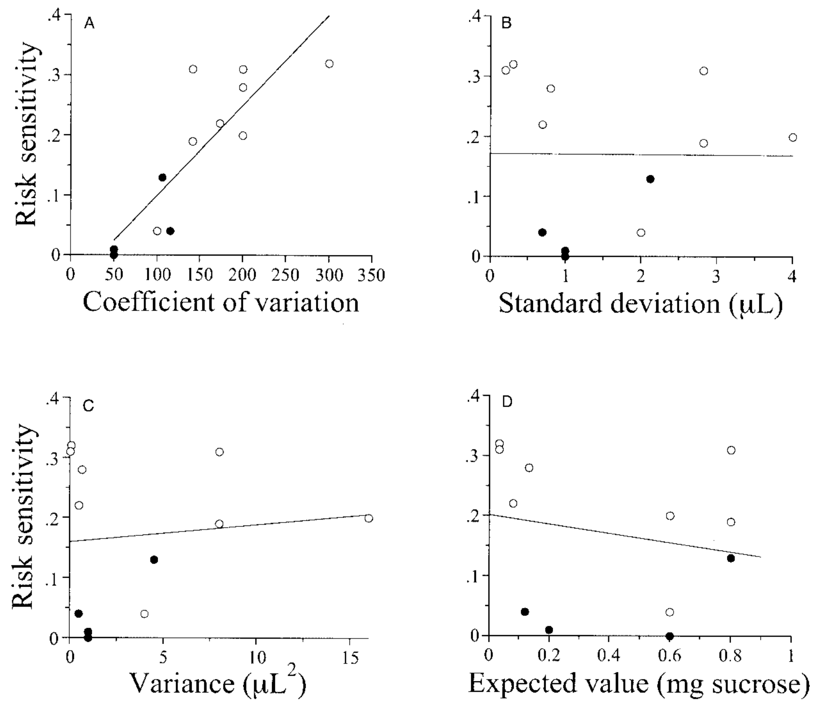

Figure 2. Risk sensitivity (|p(ST) − .5|) of bees and wasps to variability in nectar volume as a function of the coefficient of variation (A), the standard deviation (B), the variance (C), or the expected value (D) of choice alternatives. Experiments with empty (zero) outcomes are shown as open circles; those without empty (zero) outcomes are shown as solid circles. A, B, and C are from "Risk-Sensitive Foraging: The Effect of Relative Variability," by S. Shafir, 2000, *Oikos, 88,* p. 667. Copyright 2000 by Blackwell. Reprinted with permission.

.0001, and absolute gain versus absolute loss, $F(1, 201) = 26.82$, $p < .0001$, in separate regressions. When both predictors were included in the same regression, the respective statistics were $F(1, 223) = 91.57$, $p < .0001$ (relative gain vs. relative loss), and $F(1, 201) = 0.51$, $p < .48$ (absolute gain vs. absolute loss). We thus ran two separate regressions for choice situations framed as relative gain versus relative losses and examined the effect of the absolute sign of outcomes (absolute gains vs. absolute losses) within each analysis.[9]

The results are shown in Table 2. For choices between options framed as gains, the set of predictor variables accounted for 66% of the variance in p(ST). For choices between options framed as losses, the regression accounted for 59% of the variance. Tables 2 and 3 show F values and significance levels for Type III sums of squares (SS), which assess the marginal contribution of the predictor given that all other listed variables are in the regression equation. We use a significance level of .05 throughout. Table 2 also reports the partial eta-squared as measure of effect size, that is, $SS_{\text{effect}}/(SS_{\text{effect}} + SS_{\text{error}})$, using the Type III SS_{effect}.

The most important result for the purposes of this article is that the CV was a significant predictor of risk taking in both the gain and the loss domains. In the domain of gains, a larger CV was associated with a greater proportion of choices of the sure option. The effect went in the opposite direction in the domain of losses, in which a larger CV was associated with a smaller proportion of choices of the sure option.

The gender of respondents did not affect choice significantly, partly because of a lack of variation in the predictor variable. As shown in Table 1, few investigators report choice behavior separately as a function of respondents' gender. Age affected choices in the loss domain, with older adults being more risk seeking than younger adults. Nationality of respondents affected choices in the loss and the gain domains. Americans were less risk seeking for losses and more risk averse for gains than respondents of other nationalities (Japanese, Dutch, British, and Chinese).

Similar to the animal data, the presence of a zero outcome had no effect on either gain or loss choices. The skewness of the risky option (p(low outcome)) affected risk taking to a very sizable degree for gain choices, and the interaction of p(low outcome) with CV was significant for both gain and loss choices. The nature of the interaction was consistent with previous observations that risk perception is more sensitive to outcome variation below the mean (which is larger in outcome distributions that are negatively skewed) than to outcome variation above the mean (which is larger in outcome distributions that are positively skewed; Bontempo, Bottom, & Weber, 1997; E. U. Weber, 1988).

Whether choices were purely hypothetical or involved real payoffs had a significant effect for both gains and losses and a sizable effect size, especially for losses, with real payoffs resulting in greater risk aversion for choices involving gains and less risk seeking for choices involving losses. Receiving an upfront pay-

[9] Diminishing marginal sensitivity to additional gains as well as losses predicts risk aversion in the domain of gains and risk seeking in the domain of losses.

Table 1
Listing of Choice Pairs Included in the Meta-Analysis of Human Choice Data

Authors and no. of choice pairs	Average *N*	Gender	Age	Nationality	Decision domain	Outcome frame	Zero outcome	Hypothetical decision	Advance payment
Kahneman & Tversky, 1984									
1	152	B	C	American	Human lives	Gains	Y	Y	N
1	155	B	C	American	Human lives	Losses	Y	Y	N
1	150	B	C	American	Money	Losses	Y	Y	N
Highhouse & Paese, 1996									
2	54	B	C	American	Jobs	Gains	Y	Y	N
2	54	B	C	American	Jobs	Losses	Y	Y	N
2	45	B	C	American	Money	Gains	Y	Y	N
2	45	B	C	American	Money	Losses	Y	Y	N
Takemura, 1993									
2	79	B	C	Japanese	Money	Gains	Y	Y	N
2	79	B	C	Japanese	Money	Losses	Y	Y	N
Takemura, 1994									
4	45	B	C	Japanese	Human lives	Gains	Y	Y	N
4	45	B	C	Japanese	Human lives	Losses	Y	Y	N
Fagley & Miller, 1990									
2	33	M	C	American	Human lives	Gains	Y	Y	N
2	41	F	C	American	Human lives	Gains	Y	Y	N
2	35	M	C	American	Human lives	Losses	Y	Y	N
2	41	F	C	American	Human lives	Losses	Y	Y	N
2	33	M	C	American	Student lives	Gains	Y	Y	N
2	41	F	C	American	Student lives	Gains	Y	Y	N
2	35	M	C	American	Student lives	Losses	Y	Y	N
2	41	F	C	American	Student lives	Losses	Y	Y	N
Wang, 1996									
4	31	B	C	American	Human lives	Gains	Y	Y	N
4	31	B	C	American	Human lives	Losses	Y	Y	N
1	33	B	C	American	Lives of relative	Gains	Y	Y	N
1	31	B	C	American	Lives of relative	Losses	Y	Y	N
4	42	B	C	American	Paintings	Gains	Y	Y	N
4	40	B	C	American	Paintings	Losses	Y	Y	N
4	34	B	C	American	Money	Gains	Y	Y	N
4	31	B	C	American	Money	Losses	Y	Y	N
Fagley & Miller, 1987									
1	44	B	C	American	Human lives	Gains	Y	Y	N
1	42	B	C	American	Human lives	Losses	Y	Y	N
van Schie & van der Plight, 1990									
2	117	B	C	British	Human lives	Losses	N	Y	N
2	88	B	C	British	Time	Losses	N	Y	N
4	48	B	C	Dutch	Human lives	Losses	N	Y	N
2	48	B	C	Dutch	Jobs	Losses	N	Y	N
Wang & Johnston, 1995									
5	46	B	C	American	Human lives	Gains	Y	Y	N
5	46	B	C	American	Human lives	Losses	Y	Y	N
1	50	B	C	American	Lives of relative	Gains	Y	Y	N
1	50	B	C	American	Lives of relative	Losses	Y	Y	N
Leclerc, Schmitt, & Dubé, 1995									
3	97	B	C	American	Time	Losses	N	Y	N
1	47	B	C	American	Time	Gains	N	Y	N
1	36	B	C	American	Money	Losses	N	Y	N
Schneider, 1992									
9	25	B	C	American	Human lives	Gains	Y	Y	N
9	20	B	C	American	Human lives	Losses	N	Y	N
6	25	B	C	American	Animal lives	Gains	Y	Y	N
6	20	B	C	American	Animal lives	Losses	N	Y	N
3	25	B	C	American	Student lives	Gains	Y	Y	N
3	25	B	C	American	Student lives	Losses	N	Y	N
6	20	B	C	American	Jobs	Gains	Y	Y	N
6	25	B	C	American	Jobs	Losses	N	Y	N
3	20	B	C	American	Money	Gains	Y	Y	N
3	25	B	C	American	Money	Losses	N	Y	N
Highhouse & Yuce, 1996									
1	118	B	C	American	Human lives	Gains	Y	Y	N
1	112	B	C	American	Human lives	Losses	Y	Y	N

Table 1 (*continued*)

Authors and no. of choice pairs	Average *N*	Gender	Age	Nationality	Decision domain	Outcome frame	Zero outcome	Hypothetical decision	Advance payment
Thaler & Johnson, 1990									
3	111	B	C	American	Money	Gains	N	N	N
2	111	B	C	American	Money	Losses	N	N	N
1	111	B	C	American	Money	Losses	Y	N	N
2	46	B	O	American	Money	Gains	N	Y	N
2	58	B	O	American	Money	Losses	N	Y	N
Laughhunn & Payne, 1984									
8	39	B	O	American	Money	Gains	N	Y	Y
8	39	B	O	American	Money	Gains	N	Y	N
Schoemaker, 1990									
1	214	B	O	American	Money	Gains	Y	Y	N
1	214	B	O	American	Money	Losses	Y	Y	N
Musser & Patrick, 1995									
4	108	B	O	American	Money	Gains	Y	Y	Y
4	108	B	O	American	Money	Losses	Y	Y	Y
Kahneman & Tversky, 1979									
1	70	B	Mix	Israeli	Money	Gains	Y	Y	Y
1	70	B	Mix	Israeli	Money	Losses	Y	Y	Y
1	72	B	Mix	Israeli	Money	Gains	Y	Y	N
1	72	B	Mix	Israeli	Money	Losses	Y	Y	N
Hsee & Weber, 1997									
5	73	B	C	American	Money	Gains	Y	Y	N
5	73	B	C	American	Money	Losses	Y	Y	N
2	82	B	C	Chinese	Money	Gains	Y	Y	N
2	76	B	C	Chinese	Money	Losses	Y	Y	N
Loomes, Starmer, & Sugden, 1989									
5	31	B	O	British	Money	Gains	N	N	N
1	31	B	O	British	Money	Gains	Y	N	N
Battalio, Kagel, & Jiranyakul, 1990									
3	32	B	C	American	Money	Losses	Y	Y	N
3	32	B	C	American	Money	Losses	Y	N	Y
2	31	B	C	American	Money	Gains	Y	Y	N
1	33	B	C	American	Money	Gains	N	Y	N
2	30	B	C	American	Money	Gains	Y	N	Y
5	31	B	C	American	Money	Gains	N	N	Y

Note. B = both male and female; M = male; F = female; C = college students; O = Older adults; Mix = Mixture of college students and older adults; Y = yes; N = no.

ment before making a (financially)[10] risky decision had a significant effect on choices involving gains and more strongly losses, making respondents more risk seeking, consistent with Thaler and Johnson's (1990) house-money effect.

The substantive domain of the decision (e.g., money vs. human lives) had a significant and very sizable effect on risk taking for choices in the gain domain, in which choices involving gains in human lives were less risk averse than choices involving other outcome dimensions, and even more so in the loss domain, in which choices between options involving the loss of human lives were more risk seeking.

To compare the ability of the CV of the risky choice alternatives to predict risk sensitivity with that of their variance (or SD) following Shafir's (2000) lead, we restricted our regression analyses to choices between monetary outcomes; therefore, we are not restricted to dimensionless quantitative predictors such as the CV. Table 3 provides a summary of six different regression analyses, each of which was run separately for (a) choices involving financial gains and (b) choices involving financial losses. The first three regression models use the same predictor variables used in the regression analysis of the full choice set in Table 2, with the following exceptions. Gender was not reported in any of the studies involving monetary lotteries and thus could not be used as a predictor, and domain dropped out because we restricted this analysis to a single content domain, money. The first three regression models differed only in their measure of outcome variability or risk: The first one (reported in the leftmost column) uses the CV as its measure of risk, the second regression (reported in the middle column) uses the variance as its measure of risk, and the third regression (reported in the rightmost column) uses the SD as its measure of risk. The proportion of variance accounted for by each of the three regressions is reported in the table note. *F* values and *p* values of all predictor variables other than risk and its interaction with *p*(low outcome) are very similar for all three regressions and are thus only reported for the first one. The second set of three regression models was identical to the first set but added the EV of the choice pair to each of the first three regression

[10] Upfront payment was provided only for financial risky choices.

Table 2
Results of Regression Analysis of Proportion of Respondents Choosing the Sure-Thing Option, Including All Decision Content Domains

Source	*df*s	*F*	*p*	Effect size
Choices between gains, $R^2 = .66$				
Gender	2, 97	2.60	.08	.05
Age	2, 97	1.19	.31	.02
Nationality	3, 97	4.85	.004	.13
Absolute outcome sign	1, 97	2.67	.11	.03
Advance payment	1, 97	6.11	.02	.06
Outcomes for real	1, 97	5.67	.02	.06
Domain	7, 97	3.54	.002	.20
p(low outcome)	1, 97	26.37	$< .0001$	.21
Zero outcome	1, 97	0.44	.50	.00
CV	1, 97	12.19	.0007	.11
p(low) × CV	1, 97	14.30	.0003	.13
Choices between losses, $R^2 = .59$				
Gender	2, 85	0.76	.48	.02
Age	2, 85	3.87	.03	.08
Nationality	3, 85	3.85	.007	.16
Absolute outcome sign	1, 85	2.42	.17	.03
Advance payment	1, 85	9.24	.003	.10
Outcomes for real	1, 85	22.14	$< .0001$	.21
Domain	7, 85	10.48	$< .0001$	.47
p(low outcome)	1, 85	2.03	.15	.02
Zero outcome	1, 85	0.39	.53	.00
CV	1, 85	6.11	.02	.07
p(low) × CV	1, 85	6.12	.02	.07

Note. The reported effect size is the partial eta-squared, that is, $SS_{effect}/(SS_{effect} + SS_{error})$, using the Type III SS_{effect}. CV = coefficient of variation; *SS* = sums of squares.

equations.[11] The *F* value and *p* value of this additional predictor variable are also shown in Table 3.

In the gain domain, use of the CV as a predictor of risk taking in conjunction with the other predictor variables shown in Table 3 resulted in an R^2 of .62. Using the same set of predictors in combination with the variance or SD of outcomes, respectively (instead of the CV), reduced the R^2 to .52 and .53. Although all three measures of risk were significant predictors, partial eta-squared effect size was .16 for the CV and only .09 for the variance and SD. In the loss domain, the R^2 was .59 for the regression involving the CV and .56 and .58 for the regressions involving the variance or SD, respectively. None of the three measures of risk reached conventional significance, but the CV reached a level of marginal significance.

Whether outcomes were hypothetical or real affected risk sensitivity for monetary gains and especially for monetary losses. Real financial outcomes made respondents more risk averse for gains and less risk seeking for losses, that is, a main effect (shift) in the direction of less risk taking for both gains and losses. The skewness of outcomes in the risky option (*p*(low outcome)) affected risk taking in the domain of gains, in which greater downside variability resulted in increased risk aversion, all other things being equal. For neither gains nor losses, did any of the three measures of variability or risk interact with the skewness of outcomes (risk × *p*(low outcome)).

Adding the expected value of each choice pair to the regression equations shown in Table 3 did not significantly improve our ability to predict risk sensitivity, except for a small but significant effect for gain choices, using the CV as the measure of risk. Thus Dyer and Jia's (1997) hypothesis (mentioned in Footnote 5) that degree of risk sensitivity might depend on the EV of choice options seems to hold only for gain choices.

In summary, our meta-analysis of human risky choice studies showed the CV to be a significant predictor of risk sensitivity across a broad range of risky choice content domains. When examined in the context of only risky financial decisions, however, the CV proved to be only a marginally better predictor of choices than more conventional measures of variability or risk, such as the variance, especially in the gain domain. Other variables predicted risk sensitivity far more successfully, including whether outcomes were real or hypothetical and the presence of a zero outcome, consistent with aspiration level effects (Lopes & Oden, 1998). The results implicating the CV as a predictor of human risk sensitivity for financial decisions were clearly not as compelling as those of the meta-analysis of the animal data. To test a potential explanation for this discrepancy, we conducted the following two experiments.

Experiment 1

Learning Outcome Value and Probability by Experience

In this study, we tried to recreate as closely as possible the learning conditions of an animal in a typical risky foraging study. Without the benefit of symbolic representation and transmission of vicarious experience that allows human experimenters to inform human decision makers about choice outcomes and their likelihood by statements such as "a 20% chance of winning $100, otherwise nothing," nonhuman animals need to acquire information about the magnitude and likelihood of outcomes in different choice alternatives through repeated sampling and personal experience. The encoding and use of outcome and likelihood information are liable to be different under those two conditions, and the processes that give rise to risk sensitivity that is proportional to the CV may more likely operate under sequential sampling and associative learning. Every single one of the 226 data points analyzed in the meta-analysis of the human data came from studies that presented choice alternatives in a summarized, symbolic fashion, using either a numeric format (e.g., [$20, .1; $0, .9] vs. $2 for sure, indicating a choice between a lottery that paid $20 with a probability of .1 or nothing with the remaining probability of .9 and a sure gain of $2) or a spinner wheel or bar chart to describe outcomes and their probabilities. We hypothesized that the advantage of the CV over variance as a predictor of human risk sensitivity would be stronger in situations in which human respondents acquire information about risky choice options experientially and over time.

[11] We included both the EV and the CV to test for the possibility that risk sensitivity might depend on the EV of the choice options as hypothesized by Dyer and Jia (1997). Although the inclusion of EV as predictor in its own right and as the denominator term in CV might result in multicollinearity problems for some data sets, this was not true for the present set of choice options. Correlation between EV and CV was not significant (with an *r* of −.07 and −.11, respectively) for both gains and losses.

Table 3
Results of Regression Analysis of Proportion of Respondents Choosing the Sure-Thing Option in Choices Involving Monetary Outcomes

		Risk = CV		Risk = variance		Risk = SD	
Source	*df*s	*F*	*p*	*F*	*p*	*F*	*p*
Choices between financial gains[a]							
Age	1, 50	2.78	.11				
Nationality	3, 50	4.19	.01				
Absolute outcome	1, 50	1.93	.17				
Advance payment	1, 50	6.80	.02				
Outcomes for real	1, 50	4.71	.04				
p(low outcome)	1, 50	5.27	.03				
Zero outcome	1, 50	1.79	.20				
Risk	1, 50	9.25	.004	5.06	.03	4.95	.03
p(low) × risk	1, 50	2.84	.10	1.63	.28	0.08	.78
Adding EV to above:							
EV	1, 50	5.09	.03	2.49	.12	0.03	.87
Choices between financial losses[b]							
Age	1, 27	5.59	.03				
Nationality	2, 27	0.02	.98				
Absolute outcome	1, 27	0.20	.66				
Advance payment	1, 27	6.32	.02				
Outcomes for real	1, 27	20.52	.0001				
p(low outcome)	1, 27	0.44	.52				
Zero outcome	1, 27	1.26	.27				
Risk	1, 27	3.12	.09	0.79	.38	2.01	.17
p(low) × risk	1, 27	0.05	.83	0.58	.45	1.26	.27
Adding EV to above:							
EV	1, 27	0.70	.41	1.94	.18	0.54	.47

Note. CV = coefficient of variation; SD = standard deviation; EV = expected value.
[a] Risk = CV, $R^2 = .62$; Risk = variance, $R^2 = .52$; Risk = SD, $R^2 = .53$. [b] Risk = CV, $R^2 = .59$; Risk = variance, $R^2 = .56$; Risk = SD, $R^2 = .58$.

Method

Undergraduate students at the Ohio State University came to an experiment on risky decision making that advertised that participants could win money as a function of their decisions and preferences. Each of the 110 participants went through the following sequence of events in a one-on-one session with an experimenter. The experimenter presented the participant with two decks of cards, each deck consisting of 50 cards. The deck to the left was labeled L, and the one to the right was labeled R. Respondents were told that they had the opportunity to sample cards from the two decks, in any order they desired, until they had a good idea which of the two decks was "better," in the sense that they would prefer to draw from it during a trial known to involve real monetary payoffs. Any card that was turned over revealed a money amount that would be won as the result of drawing the card. Respondents sampled at their leisure by pulling a card randomly from the deck and replacing it afterward; with no explicit instructions about the number of cards to sample, they drew on average about 20 cards from the two decks. At the end of this sampling period, respondents indicated to the experimenter from which deck (L or R) they preferred to draw a card for the real-payoff trial. Unbeknownst to the respondents, the cards in one of the two decks all had the same positive payoff ($\$x$), whereas the cards in the other deck provided two different payoffs, one zero (\$0) and the other a larger positive payoff ($\$y$, $y > x$). The two decks had equal EVs. Respondents received no information about outcome magnitudes or probabilities other than what they obtained by sampling cards from the two decks.

The experimenter shuffled the deck that was chosen by the respondent, who then drew a card at random. The obtained payoff was noted before the respondent moved on to a new pair of decks for which the sampling and decision procedure was repeated. Respondents indicated their preferred deck from five pairs of decks, respectively, in this way; drew a card from each of the preferred decks; and finally rolled a die that determined for which of the five obtained outcomes they would receive an actual monetary payoff.[12]

The possible outcomes, their probabilities, and expected values of the five choice pairs are shown in Table 4. The position of the constant payoff deck as the L or R deck was counterbalanced across pairs and respondents. The five choice pairs included in the study were selected in such a way that the variable payoff decks of three of the choice pairs were equal in variance but differed in CV (through a change of skew transformation), whereas another set of three were equal in CV but differed in variance (through a change of scale transformation). Just as in the meta-analyses reported above, both choice alternatives (the two decks) had equal EV, leading again to the prediction that the proportion of respondents choosing the constant payoff deck (p(ST)) should be a (positive) linear or perhaps logistic function of the perceived riskiness of the variable-payoff deck. Our design allowed us to see very clearly whether variance or CV is a better measure of perceived risk in the sense of better predicting differences in risk sensitivity and choice.

[12] Respondents were paid for only one of their choices at the end of the experiment to prevent house-money and other "wealth" effects.

Table 4
Description of Choice Pairs Used in Experiments 1 and 2 and Hertwig et al. (in press) and Observed Proportions of Choices of Sure Thing, p(ST)

Choice pair			Gamble		Experiment 1	Model prediction		Experiment 2
ID	Sure thing	Gamble	Variance	CV	p(ST)	FA[a]	DD + FA	p(ST)
				Experiments 1 and 2				
1	\$1	\$0, .9; \$10, .1	9	300	.68	.69 (.03)	.79	.40
2	\$3	\$0, .5; \$6, .5	9	100	.39	.59 (.05)	.59	.25
3	\$9	\$0, .1; \$10, .9	9	33	.24	.51 (.05)	.34	.72
4	\$1	\$0, .5; \$2, .5	1	100	.58	.55 (.03)	.55	.24
5	\$3	\$0, .5; \$6, .5	9	100	.39	.59 (.05)	.59	.25
6	\$6	\$0, .5; \$12, .5	36	100	.42	.61 (.05)	.61	.45
				Hertwig et al.				
7	\$1	\$0, .9; \$10, .1	9	300	.76	.69 (.03)	.79	
8	\$9	\$0, .1; \$10, .9	9	33	.22	.51 (.05)	.34	
9	\$3	\$0, .9; \$32, .1	92	300	.80	.82 (.03)	.88	
10	\$3	\$0, .2; \$4, .8	3	50	.12	.52 (.04)	.46	

Note. In Experiment 1, the observed response proportions for the sure-thing option (p(ST)) were under experience-based choice, and in Experiment 2, they were under description-based choice. CV = coefficient of variation; FA = fractional adjustment; DD + FA = dominance-detection augmented FA.
[a] The standard error of the estimate is shown in parentheses.

Results

Visual inspection and statistical analysis of the choice proportions shown in the top of Table 4 confirm our prediction that risk aversion increases with the CV, $r(4) = .84$, $p < .08$, rather than with the variance of outcomes, $r(4) = -.22$, *ns.* Just as for the monetary gain decisions in the meta-analysis of human choices, the EV of the options of the choice pair also affected the likelihood of choosing the sure thing, in the direction that respondents were less risk averse for greater EV, $r(4) = -.90$, $p < .05$. However, the CV predicts choice proportions even when EV is in the regression equation, with an increase in R^2 from .80 to .91. Variance, conversely, does not predict choice proportions, either by itself or on the margin of EV.

Modeling of Results

March (1996) recently examined some classic associative learning models for their ability to account for risk preference (i.e., risk aversion for gains and risk seeking for losses) in situations that closely parallel the conditions of Experiment 1. The models were simple reinforcement learning rules dating back to the 1950s that assume that people change their propensity to choose an option from an initial starting point (e.g., indifference in the case of pairwise choice) as a function of outcome feedback they receive. The model that provided the best fit was the fractional adjustment (FA) model, a variation on the classic Bush and Mosteller (1955) and Estes (1959) stochastic learning model. The use of simple learning rules to predict behavior in risky environments has also been of interest in the animal literature (Hammer & Menzel, 1995; Montague, Dayan, Person, & Sejnowski, 1995).

For the set of choice pairs used in Experiment 1, we simulated the propensity to choose the sure thing predicted by the FA model, assuming 20 learning trials (the average number of cards sampled by our respondents). Initial choice propensities for the two options in each pair were assumed to be .5 because decision makers had no information about either of the two options. The probability of choosing option i at time $t + 1$ (i.e., $p_{i,t+1}$) changes as the result of the action taken at time t and the outcome then obtained. After a favorable outcome, the choice probability increases; after an unfavorable outcome, it decreases. The increment of change is a proportion (α, $0 \leq \alpha \leq 1$) of the propensity not to choose option i on trial t (i.e., $1 - p_{i,t}$):

$$p_{i,t+1} = p_{i,t} + \alpha(1 - p_{i,t}). \tag{4}$$

The greater the learning rate parameter α, the faster the change. In addition, the change in choice propensity depends on the magnitude of the (favorable) outcome x. For the two-alternative positive-outcome choice problems of Experiment 1, this can be expressed as

$$p_{i,t+1} = 1 - [(1 - \alpha)^x (1 - p_{i,t})]. \tag{5}$$

When $x = 0$, Equation 5 predicts that $p_{i,t+1} = p_{i,t}$. The value of $p_{i,t+1}$ determines the probability of choosing option i on the next trial, at which point the fractional adjustment continues recursively.

A systematic search of the parameter space showed that a value of $\alpha = .14$ provided the best fit (using a least-squares criterion) of the FA model to the choice proportions for the sure-thing option in the five choice pairs of Experiment 1. The choice probabilities predicted by the FA model based on the average of 2,000 simulation runs (equivalent to the proportion of sure-thing choice in a sample of 2,000) are shown in Table 4. Also shown (in parentheses) is the standard error of that estimate for the sample size of Experiment 1 (namely, $N = 110$). The FA model choice probabilities correlated very highly with the CV of the gamble of each pair across the five choice pairs, $r(4) = .93$, $p < .03$, but not with the variance, $r(4) = .23$, *ns.*

There was a sizable (although because of the limited sample size not significant) correlation between the FA model predictions and the observed choice proportions across the five choice pairs, $r(4) = .73$, $p < .16$, but visual comparison of observed and predicted choice proportions suggests room for improvements. The FA model tends to predict a level of risk aversion higher than observed for several of the choice pairs, and this is particularly true for Pair 3 and to some extent for Pairs 5 and 6. Its updating and choice algorithm, in fact, prevents it from predicting any level of risk seeking (i.e., $p(\mathrm{ST}) < .5$), given equal EV of choice options and indifference between the two options as a starting propensity. Although capturing the updating of choice propensity on the basis of payoff experience, associative learning models (such as the FA model) fail to reflect other (higher order) cognitive processes such as inferences or counterfactual comparisons. Modern learning models frequently try to combine the power of such models with insights of the cognitive revolution that followed them.[13] In this spirit, a learning model of human choice propensity in risky choice environments based on (oftentimes) limited sampling requires some augmentation beyond simple associative processes. One obvious addition is people's response to the detection of (apparent) dominance of one choice alternative. Especially in choice situations like Choice Pairs 1 and 3 of Experiment 1, in which one outcome of the gamble is a rare event, there is a nonnegligable chance that this outcome will never be sampled. Given a probability of .9 of obtaining $0 in the gamble of Choice Pair 1, for example, the probability of never sampling the $10 outcome in 10 trials is .35. When confronted with 10 instances of obtaining $1 from Choice Option 1 and 10 instances of obtaining $0 from Choice Option 2, human respondents will respond to this apparent dominance by choosing Option 1 with a probability of 1.0; that is, they will react to apparent dominance far stronger than predicted by purely associative processes. The dominance-augmented FA model, whose predictions are also shown in Table 4, thus adds the assumption that the 35% of decision makers who can be expected never to experience the rare outcomes in Choice Pairs 1 and 3 will all choose the dominating option and that the remaining 65% of decision makers will choose according to the associative rules of the FA model.[14] The dominance-augmented FA model predictions provide a better fit to the observed experience-based choice data, $r(4) = .85$, $p < .06$, and again correlate significantly with the CV, $r(4) = .90$, $p < .04$, but not with the variance of the risky choice option, $r(4) = .13$, *ns.*

The experience-based choice proportions of Experiment 1 deviated from the predictions of prospect theory (Tversky & Kahneman, 1992), a modified version of expected utility theory designed to account for a wide range of single (nonrepeated) decisions between options whose outcomes and their probabilities are usually described symbolically. Pair 3, for example, is a choice pair usually chosen to illustrate the certainty effect, that is, the phenomenon that people strongly weight the certainty of a sure option because most people choose the sure thing of $9 over the lottery. To see the extent to which choice behavior would differ for the choice pairs shown in Table 4 when people choose on the basis of described (symbolic and vicariously learned) information about outcomes and probabilities, we conducted Experiment 2.

Experiment 2

Method

A different sample of 55 Ohio State University undergraduate students came to an experiment advertised and conducted in a fashion parallel to that of Experiment 1, with the following exception. Rather than having to sample from the two decks from which they would ultimately draw a card for real payoff, respondents were given full information about probabilities and payoffs of both choice alternatives in the form of two pie charts that presented probability information numerically and pictorially and outcome information numerically. As before, respondents provided their preference for each of the five pairs of decks and then drew a card from the preferred deck. Just as in Experiment 1, they then rolled a die that determined for which of the five obtained outcomes they would receive an actual monetary payoff.

Results

The proportions of respondents (out of 55) who chose the sure thing in each of the five pairs in Experiment 2 when outcome information was given rather than acquired by experience are shown in the top of Table 4. Choices were quite different, especially for the two choice pairs (1 and 3) with skewed gambles. As predicted by prospect theory, respondents were now risk averse for Pair 3. The correlation between the five choice proportions $p(\mathrm{ST})_i$ observed in Experiment 1 and those observed in Experiment 2 was $-.60$.

Other Studies

Hertwig, Barron, Weber, and Erev (in press) investigated behavior under repeated sampling for two of the five choice pairs used in Experiment 1 and essentially replicated our results. The proportion of respondents (out of a sample of 26 Israelis recruited for an experiment at the Technion in Haifa, Israel) who chose the sure thing was .76 (compared with our result of .68) for Pair 1 and .22 (compared with our result of .24) for Pair 3. Hertwig et al. used two other choice pairs comparable to the choice problems in our experiments except that the lottery in each pair had a slightly larger EV than the sure thing, as shown in the bottom of Table 4. A regression of risk sensitivity ($p(\mathrm{ST})$) for the nine choices made after learning from experience shown in Table 4 (the five choice proportions collected in Experiment 1 and the four choice proportions collected by Hertwig et al., in press) on the EV and CV of the risky option of each pair accounted for 85% of the variance, with the CV as a significant predictor, $F(1, 8) = 16.41$, $p < .007$, but not the EV, $F(1, 8) = 0.24$, $p < .64$. Regressing risk sensitivity instead on EV and variance accounted for only 66% of the variance, with EV as a significant predictor, $F(1, 8) = 7.60$, $p < .04$, and the variance as an only marginally significant predictor, $F(1, 8) = 4.06$, $p < .10$.

Summary and Discussion

Risk Sensitivity and CV

The animal and human data presented in this article suggest that risk sensitivity of human respondents and lower animals share

[13] In the context of strategic, game-theoretical interactions, for example, the learning model by Camerer and Ho (1999) assumes that, in addition to learning from past play, decision makers attempt to anticipate future play by attending to the hypothetical payoffs of strategies that were not chosen on a previous trial.

[14] Other additional higher order mechanisms could be marshaled to accommodate the observed risk seeking for Choice Pairs 5 and 6 but would take us too far away from the central question of this article, the comparison between CV and variance as predictors of risk sensitivity.

common characteristics. Both seem to be better predicted by the CV, a measure of the relative risk of risky choice alternatives, than by their variance or SD. This is especially true when information about variability is acquired by experience, that is, when respondents repeatedly sample choice alternatives and experience their outcomes. Experiential learning of outcome values and their likelihoods over time is, of course, the norm for the risky decisions made by lower animals. Many human risky decisions, however, also provide opportunity for such experiential learning, for example, the decision of whether to pack an umbrella in the morning after a look at the sky, which is influenced by such past experiences as the burden of carrying the umbrella unnecessarily and the frequency of rain. For human decisions, direct experience of past outcomes is usually also supplemented by third-party information. Our ability to symbolically represent experience, which enables us to manipulate it and communicate it to others, thus allowing for vicarious learning, probably goes a long way toward explaining the success of the human species. Symbolic information received about choice outcomes and their probabilities can derive from somebody else's personal experience (e.g., the likelihood of getting burgled in Rome during a one-year sabbatical) or from knowledge about underlying stochastic processes (e.g., gambling outcomes, weather forecasts). Investment decisions also offer the opportunity for both types of input. Although statistical (symbolic) information is available about past returns of investment options, untrained investment decisions are undoubtedly also driven by recent experiences of personal losses or gains. Overreactions to recent events are most likely mediated by (faulty) associative updating of outcome and likelihood information based on such vivid, personal experience.

That decisions based on personal experience can differ from decisions based on symbolic description of possible outcomes should not have come as a complete surprise. Work in the area of probabilistic reasoning provides precedent for the fact that different ways of obtaining information can trigger different reasoning processes, for example, frequency versus probability formats to describe the likelihood of different events (Gigerenzer & Hoffrage, 1995). One could argue that frequency formats often result in more accurate estimates of likelihood precisely because they allow people to tap into their experience-based representation of events.

Associative Learning Models and CV Sensitivity

Associative learning models, such as the FA model, that assume that risk sensitivity is shaped by outcome feedback over repeated trials make predictions for risky choices that correlate highly with the CV and far less with variance of the risky options. This result does not appear to have been noted before. March (1996) and Kacelnik and Bateson (1996) independently noted that associative learning models predict observed risk attitudes (i.e., risk aversion for gains and risk seeking for losses in human data and risk seeking for delays in animal data). Neither one of them, however, examined the degree of risk seeking or risk aversion as a function of different measures of outcome variability. Closed form solutions for associative learning model predictions of choice propensity after *n* learning trials are not readily available because of multiple sources of nonlinearity (e.g., in the use of feedback information and in sampling probabilities). However, simulations and algebraic examination of components of such models readily show that choice propensity is affected much more by changes in the skew of the outcome distribution of risky options (which affect sampling probabilities and the opportunity to observe possible outcomes) than by changes of scale (which are, by definition, identical for both choice options and thus—loosely speaking—often cancel each other out). Changes in skew for positive outcome lotteries affect the EV of a gamble without changing its variance (e.g., going from Choice Pair 1 to Choice Pairs 2 and 3 in the top of Table 4) or change its variance without changing the EV (e.g., going from Choice Pair 1 to Choice Pair 4). Either change affects the CV of the risky option, whereas only the latter change affects the variance. Changes in scale, conversely, always affect the variance of the risky option but keep the CV constant because EV and SD change by the same scale factor.

Other theories have addressed risky choice patterns that deviate from predictions of expected-utility type theories (especially under conditions of experiential learning, e.g., Busemeyer & Myung, 1992). These include Gonzales-Vallejo's (2002) proportional difference model of choice and Busemeyer and Townsend's (1993) decision field theory, which models the choice deliberation process as an accumulation of information about the consequences of a decision over time. The observation that both of these models make predictions that are consistent with the CV as the statistical predictor of risk sensitivity provides a unifying classificatory dimension to choice theories that appear quite different on the surface.

Two Paths to CV Sensitivity

In this article, we discussed two types of processes that give rise to risk sensitivity that is better predicted by the CV than the variance of risky outcome distributions. The first one is the representation of outcome values that follows Weber's law. As described in our introduction, there is fairly conclusive evidence in the animal literature for such a model of representation, which—in combination with some simple assumptions about decision processes—provides a process level explanation of choices that are functionally described by prospect theory's value function (see Marsh & Kacelnik, 2002). The prospect theory value function has been parameterized as a power function (e.g., $u(x) = x^{88}$ for gains). Like other power functions, it exhibits constant relative risk aversion, meaning that the index of risk attitude under expected utility theory $-u''(x)/u'(x)$ is a constant times $1/x$. Use of the CV to predict risk sensitivity by a measure of variability that standardizes it by dividing by EV reflects at least partly this dependence of risk attitude on *x*. To the extent that the representation of outcomes values following Weber's law is responsible for CV (rather than variance) sensitivity of risk taking, this regularity should be observed for both experience-based risky decisions and decision-based risky decisions from given information because outcome information needs to be represented in both paradigms.

This is in contrast to the other process shown in this article to lead to CV sensitivity of risk taking. Associative learning of choice propensity leads to choice behavior that correlates more strongly with the CV than with the variance of risky choice options. Such a learning process will, of course, only contribute to CV sensitivity of choice in those decision situations in which behavior is shaped by personal experience (feedback) over time.

These two processes are not mutually exclusive and most likely operate in parallel. This would account for the fact that the meta-analysis of human choice data (that reflect exclusively studies of description-based risky choice from givens) shows a much weaker relationship between the CV and risk sensitivity than the animal data meta-analysis and Experiment 1, in which the addition of associative processes could contribute to a much stronger relationship between the CV and risk sensitivity.

How to Model CV Sensitivity

The CV is a relative measure of risk that describes variability per unit of return. Introspection suggests that such standardization has face validity in describing our subjective experience of risk. A lottery with an SD of $100 seems risky when its EV is $200 but virtually a sure thing when its EV is $5 million. As mentioned in the introduction, the CV is very widely used as a measure of risk in a broad range of applied domains. The wide acceptance of EU theory as the normative model of risky choice and of its modifications such as prospect theory as the best descriptive model of risky choice may have prevented notice of the CV as a possible measure of risk in the judgment and decision making literature on risky choice. In particular, there exists no utility function such that the expected utility of lottery X can be expressed as a risk–return model with $EV(X)$ as a measure of return and $CV(X)$ as a measure of risk, along the lines spelled out by Bell (1995) and Jia and Dyer (1997). Risk–return decompositions of commonly used utility functions result in measures of risk in which the outcomes of risky option X are standardized by subtracting the option's EV: $R(X) = f[E(X - EV(X)]$. Our article suggests that a better functional representation of the measure of risk to which human and animal decision makers appear to be sensitive when making risky decisions involves a standardization that divides outcome variability by EV. Dyer and Jia (1997) showed that models that use such a measure of risk (which they called relative risk–value models) can explain many empirical choice patterns unexplained by EU theory.[15]

Our results suggest that existing deviations of human choice behavior from prescriptive models in finance and economics should be examined in light of the fact that people are responding to a different index of risk than that assumed to underlie their choices in EU-type models. Rabin (2000) recently called renewed attention to the inconsistency of risk attitudes inferred from choices between lotteries and sure-thing options at different scales, under the assumption that risk preference follows a model like expected utility or prospect theory, showing in particular that degree of risk aversion computed from small stake choices vastly (and ludicrously) overpredicts risk aversion for larger stake lotteries. Although a variety of post hoc explanations have been proposed to explain empirical choice patterns that deviate from utility-function based predictions, risk–return models of choice that use the CV as their measure of risk very naturally predict such "inconsistency" in risk attitudes for choices that differ vastly in expected value.

CV Sensitivity as an Adaptive Response to Ecological Regularities?

Our experiment and the meta-analyses of existing risky choice data reported in this article document that, descriptively, the CV dominates measures of absolute variability, such as the variance of outcomes as a predictor of risk sensitivity. We conclude with some speculations about whether such relative encoding of outcomes and their variability should be considered just a cognitive bias, as implied in Thaler's (1980) discussion of percentage framing, or whether it might also have some adaptive function that may not be immediately apparent. That relative risk perception and risk sensitivity describe human behavior and especially the behavior of lower animals suggests that the cognitive mechanisms that give rise to this regularity evolved quite a while ago and have not been selected against.

We suggest that the prevalence of highly skewed distribution function of the type

$$f(i) = (a/i^{k})b^{k}, \tag{6}$$

where a, b, and k are constants (with b usually close to unity and $1 < k < 2$) and i indexes rank order along some continuum, might make the relative encoding of variability along the lines of the CV cognitively (or information-theoretically) efficient. Zipf (1949) reported that a wide range of linguistic, sociological, biological, physical, and economic phenomena have such J-shaped distribution functions (also see Simon, 1955).[16, 17] The population size of cities in the United States, for example, drops off in Zipf-law fashion as we move from the 1st-ranked city (New York, with 7 million inhabitants in 1990: $f(1) = a/1$), to the 7th-ranked city (Detroit, with 1 million inhabitants: $f(7) = a/7$), and to the 25th-ranked city (New Orleans, with 300,000 inhabitants: $f(25) = a/25$). Although the variance (or SD) in population of the 10 highest ranked cities is very high (population drops off rapidly at the beginning, following Zipf's law), the variance of the 10 lowest ranked cities (which are almost equal in size, as a/k does not decrease appreciably for large values of k) is very low. If the objective is to maintain approximately equal discrimination between U.S. cities across the whole range, it makes sense to encode size in a way that gives rise to JNDs that follow Weber's law and to perceptions of variability that are approximated by the CV. Another example, relevant for foraging birds, is the distribution of nectar volume in plant species, which also follows a mirror-image J-shaped function (see Figure 3). Only very few plant species achieve very high volumes of nectar, so that nectar volume drops off very rapidly among the highest ranked species but increasingly less so among the lower ranked species. For one to maintain approximately equal discrimination between plant species across the whole range of nectar volumes, it makes sense to encode volume differences in a relative manner, following Weber's law (Shafir, Bechar, & Weber, 2003). Other examples of phenomena that have such J-shaped, highly skewed distribution functions are word frequencies in English and other languages, the distribution of personal incomes as first discovered by Pareto (Champernowne, 1953), company budgets, and the size of river basins and earth quakes. Explanations for the prevalence of such J-shaped (rather than bell-shaped) distribution functions are beyond the scope of

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[15] Dyer and Jia (1997) reconciled EU models and relative risk–return models in a somewhat artificial way by hypothesizing risk–return tradeoff coefficients (b) that will do so, in particular, by making b a function of $EV(X)$.

[16] Equation 6 is sometimes referred to as Zipf's law after Zipf (1949).

[17] These distribution functions are often described as J-shaped because their shape resembles the capital letter J when frequencies are plotted starting with the lowest ranks (and lowest frequencies) or as a mirror-image J when frequencies are plotted starting with the highest ranks.

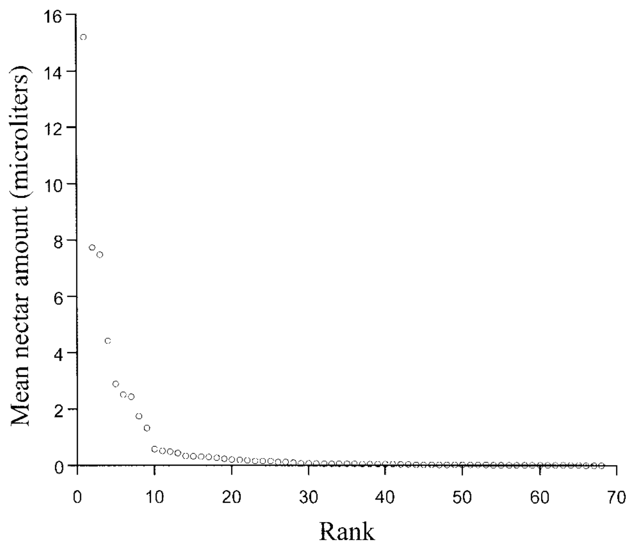

Figure 3. The distribution of mean nectar amounts according to their rank order in a particular (xeric Mediterranean) ecosystem. Data are from Petanidou and Smets (1995).

this article (but see Mandelbrot, 1953, and Simon, 1955). For our purposes, their prevalence suffices to provide a possible explanation for the development of cognitive representations of magnitudes that follow Weber's law as an adaptation to the structure of the organisms' physical and social environment.

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